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RESEARCH ARTICLE

Measures of Social Deprivation That Predict Health Care Access and Need within a Rational Area of Primary Care Service Delivery

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Objective. To develop a measure of social deprivation that is associated with health care access and health outcomes at a novel geographic level, primary care service area.
Data Sources/Study Setting. Secondary analysis of data from the Dartmouth Atlas, AMA Masterfile, National Provider Identifier data, Small Area Health Insurance Estimates, American Community Survey, Area Resource File, and Behavioural Risk Factor Surveillance System. Data were aggregated to primary care service areas (PCSAs).
Study Design. Social deprivation variables were selected from literature review and international examples. Factor analysis was used. Correlation and multivariate analyses were conducted between index, health outcomes, and measures of health care access. The derived index was compared with poverty as a predictor of health outcomes.
Data Collection/Extraction Methods. Variables not available at the PCSA level were estimated at block level, then aggregated to PCSA level.
Principal Findings. Our social deprivation index is positively associated with poor access and poor health outcomes. This pattern holds in multivariate analyses controlling for other measures of access. A multidimensional measure of deprivation is more strongly associated with health outcomes than a measure of poverty alone.
Conclusions. This geographic index has utility for identifying areas in need of assistance and is timely for revision of 35-year-old provider shortage and geographic underservice designation criteria used to allocate federal resources.
Key Words. Access to health care, primary care service areas, social deprivation

It is internationally recognized that health and health care access inequities vary along social gradients. However, targeted health resource allocation can reduce the range of disparities (Marmot 2006). Using geographic measures of the social determinants of health to guide allocation of health resources is supported by an international consensus and substantial research (Banks et al. 2006). Examples of this work can be found in the United Kingdom (UK) (Noble et al. 2008) and New Zealand (White et al. 2008). Socioeconomic inequities and the health disparities they produce are comparably worse in the United States compared with other OECD countries (Banks et al. 2006; Schoen et al. 2009), indicating that U.S. policies designed to reduce them are inadequate. However, the United States is in the process of revising decades-old geographic measures of workforce shortage and medical underservice and has an opportunity to join these Commonwealth countries in meeting this basic tenet of the World Health Organization Committee on the Social Determinants of Health.

In contrast to the United States, many OECD countries use geographic patient communities, whether assigned or self-selected, to create rational service areas that are used for monitoring population health outcomes and adjusting health care resource allocation. The United States also lacks a system of population health accountability and its methods of assigning additional resources to underserved communities, both the Health Professional Shortage Area (HPSA) and the Medically Underserved Areas (MUA), are 35 years old. The HPSA designation criteria used by Federal health agencies are based on physician to population ratios, with some adjustment for area of high needs as measured by poverty, infant mortality, or fertility; the MUA designation uses a composite index that includes physician to population ratios, poverty, infant mortality, and elderly population (Federal Register 2010). The effort now under way to revise MUA and HPSA criteria is revealing real gaps in the science of population risk assessment, particularly for small areas and measuring socioeconomic gradients, and a lack of consensus about rational service areas. Examining how we might improve how we identify socioeconomic gradients in health care need and access may go some way to addressing the health disparities observed in the United States.

Understanding how socioeconomic status (SES) influences the use and access of health services, and how the use of measures of SES to guide the distribution of resources can reduce health disparities is bedded in a large

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body of literature and theory (Penchasky and Thomas 1981; Andersen 1995; Field 2000; Hendryx et al. 2002; Wang and Luo 2005; McGrail and Humphreys 2009). The relationship between health care need, demand, supply, and access is complex. Health *need* can be understood to mean the requirement for health services, deemed reasonable, or expected within society, taking into account factors such as the socioeconomic, age, and health profile of a community. *Demand* reflects how services are used by the population, and not necessarily the underlying need. An imbalance between need, demand, and supply can result in health care access inequity (Field 2000) and consequent poor health outcomes (Andersen 1995; Hendryx et al. 2002). Poor health care access may be measured by self report, inferred through rates of avoidable hospitalization (as an indirect measure of primary health care access) or by poor health outcomes such as morbidity and mortality rates.

It is often those most marginalized and disadvantaged who suffer a greater burden of ill health and risks for ill health yet are less likely to be able to act on this and access needed care (Hart 1971; Schofield et al. 2008). Consequently, this creates a demand for more costly, reactive care rather than ideal preventative care (Dixon-Woods et al. 2006) and produces wide disparities. This suggests that measures capturing area-level disadvantage and social deprivation may be useful tools for identifying areas to which resources could be allocated to improve delivery of health services and potentially reduce health disparities. In addition to providing universal coverage, the UK allocates resources based on geographic indices of specific social deprivation (e.g., the Townsend index and Index of Multiple Deprivation) (Townsend 1987; Carstairs 1995; Noble et al. 2008) and despite having a range of social classes similar to those in the United States, they realize a much narrower range of health disparities (Banks et al. 2006). The United States could benefit from better geographic assignment of health resources as in the United Kingdom.

In the literature, two general approaches have been taken in developing area-level measures of social deprivation for resource allocation. There are those that measure social deprivation alone (Krieger et al. 2003, 2005; Eibner and Sturm 2006; Adhikari 2008; White et al. 2008), while others have constructed composite measures of resource need, including supply, social deprivation, demographics, and health status (Field 2000; Wang and Luo 2005; McGrail and Humphreys 2009). Other work in the United States has examined a range of small area measures of socioeconomic disadvantage at the census tract or block group level for health monitoring, but this has not yet been applied to practice or policy at a national level (Diez Roux 2001; Krieger et al. 2003; Bird et al. 2010).

A challenge of developing useful measures of social deprivation is identifying the geographic definitions around which it is to be built. The vast majority of small area measures of social deprivation and health need have been based on political or administrative boundaries, or less commonly through modeling using geographic information systems (GISs) based on physical distance. As mentioned previously, many OECD countries use geographic patient communities to create rational service areas that are used for monitoring population health outcomes and adjusting health care resource allocation. Rational service areas have also been used by Federal health agencies as the underpinning geography used for HPSAs and MUAs. However, monitoring and evaluation of these programs have been hindered by a lack of consistency and complete coverage between and across counties in defining the underpinning geography. In response to this, HRSA commissioned the Dartmouth group to develop rational service areas for primary care that overcame these limitations (Goodman et al. 2003). Primary care service areas (PCSAs) are utilization-based service areas for the United States and reflect the travel of Medicare beneficiaries to primary care clinicians. As such, this creates a nationwide geography based on natural patterns of care-seeking behavior by a population with generally good access to care. Some evidence suggests that PCSAs are generalizable to younger populations based on tests with Medicaid and commercial claims (Goodman and Wright-Slaughter 2004). PCSAs offer approximations of primary health care service areas that cover the entirety of the United States that are potentially useful for identifying health care need, allocating resources, and evaluating the impact.

The aim of this article is to determine whether a measure of social deprivation can be identified that has a statistically significant relationship with health care access and health outcomes within a rational area of primary care service. We begin by constructing a social deprivation index (SDI) that can be applied nationally to small geographies. We then incorporate the SDI with other measures of access and need into regression models to examine the robustness of our measure. Finally, our index is compared with a simple measure of poverty, the single measures of social deprivation used in current underservice designations, to determine whether a composite measure improves prediction of health outcomes. We hope that such a measure might be a useful contribution to efforts to monitor population health and perhaps guide the allocation of resources in ways that could reduce disparities and improve outcomes.

METHODOLOGY

Data and Measures

Measures of Social Deprivation. Variables of social deprivation were selected on the basis of literature review and international examples. Particularly important to this analysis is the work by Field (2000) and Wang and Luo (2005). Fields identified predictors of access to health service based on a survey of doctors and patients in the United Kingdom. The model developed by Wang and Luo calculated physician supply rates for a novel geography based on travel time to health service providers, then adjusted these rates for measures of health need, as defined by socioeconomic and demographic variables (selected also on the basis of Fields' works and Ricketts' HPSA designation methodology) (Ricketts et al. 2007). Our analysis includes the key socioeconomic and demographic variables identified by Field (2000) and Wang and Luo (2005).

One of our intentions in constructing an SDI was to use readily available and easily updated national area-level data. With this approach, what is lost in specificity is gained in reproducibility. The main source of sociodemographic measures is from the Census Bureau, mainly the 2005–2009 American Community Survey (ACS) 5-year estimates (http://www.census.gov/acs/www/). These include percent living in poverty, black, less than 12 years of schooling, single parent households, and single occupant households. Following Wang and Luo (2005), we constructed a high needs measure, based on ACS data, consisting of the percent of the population (1) under the age of 5 and (2) female between the ages of 15 and 44. We considered models that also included persons older than 65 but found this measure is negatively associated with other indicators of deprivation. We also considered measures from the Townsend index: percent living in overcrowded conditions (more persons in a dwelling unit than number of rooms), percent of households without a car, and percent of 18- to 64-year olds that are unemployed, all of which are available from the ACS. Percent nonemployed was also examined. The factor loading of percent nonemployed was substantially higher, so the percent unemployed was dropped.

All these ACS measures are collected at the block group or census tract level. PCSAs are combinations of Zip Code Tabulation Areas, which in turn are composed of Census blocks. By assuming homogeneity across blocks within a block group or census tract, we used information from lower level geographies to create PCSA-level measures (see http://knox.dartmouth.edu/pcsa/downloads/Defining_PCSAs.pdf for a description of the Dartmouth

Atlas methodology). There are a total of 6,542 PCSAs in the United States and we had complete data for all but four.

Health Outcome Measures. We used four health outcome measures: mortality, infant mortality, low birth weight rates, and prevalence of diabetes. County-level mortality rates were obtained from the Center for Disease Control and Prevention (CDC) Wonder system (http://wonder.cdc.gov/wonder). We selected age-adjusted death rates for Hispanics and for non-Hispanic blacks, whites, and other races based on data pooled across 3 years (2005–2007). For counties where race/ethnicity-specific rates are unavailable, the overall county mortality rate was used instead. Low birth weight and infant mortality rates are collected by the National Center for Health Statistics and available on an annual basis in the Area Resource File (ARF). From the 2008 ARF, we used 2003–2005 low birth weight rates reported separately for whites and nonwhites and 2001–2005 infant mortality rates reported separately for whites, blacks, and other race groups. As above, for counties where race/ethnicity-specific rates are unavailable due to no births for a particular group, the overall county rates were used. We first obtained block level rates by combining race/ethnicity-specific rates at the county level with ACS population counts by race/ethnicity available at the block group level by assuming that these rates were similar at the block level. We then obtained PCSA-level rates by aggregating block-level information. The use of racial and ethnic specific rates is a possible limitation, but the choice is dictated by the available national data—mortality, infant mortality, and low birth weight rates are not available by other parameters, such as income level or other demographic characteristics.

In addition, we used 2008 BRFSS-based county-level estimates of the prevalence of diabetes available from the CDC. This measure is based on Bayesian multilevel modeling techniques that use information from nearby counties in making estimates for one county (http://apps.nccd.cdc.gov/ddt_strs2/nationaldiabetesprevalenceestimates.aspx). The 2008 estimate is based on 3 years of data (2007–2009) to improve the precision of county-level estimates. Unlike the three other health outcome measures, these estimates are not available for subpopulations within counties. County diabetes rates were used to define block rates, which were then aggregated to the PCSA level. The final step was to convert the four health measures to centile rankings.

Measures of Access. The AMA Masterfile (2010) is a relatively complete list of all physicians in the United States and includes specialty codes and physician addresses. Primary care physicians are defined as those with a primary specialty of family medicine, general practice, pediatrics, general internal medicine, and geriatrics. Our counts are restricted to active providers, that is, those engaged in direct patient care.

To obtain counts of nurse practitioners (NPs) and physician assistants (PAs), we used 2010 National Provider Identifier (NPI) data collected by the Center for Medicare and Medicaid Services (https://www.cms.gov/national providentstand/06a_datadissemination.asp). The NPI enumerates all providers who bill Medicare and Medicaid, as well as a growing number of private insurance companies. Because specialty information for NPs and PAs is limited, making it impossible to identify those working in primary care, we used their addresses to identify their co-location with physicians to assign primary care status. Specifically, if NPs/PAs worked only with primary care physicians, we assumed they were also primary care providers. If they worked only with subspecialist physicians, we assumed they were not primary care providers. If they worked with a mix of subspecialist and primary care physicians, we used the percent of these physicians in primary care to assign a probability of being primary care to the NP or PA. Finally, in cases where they were not collocated with any physicians, we assumed they worked in primary care.

Provider addresses were geocoded, allowing us to calculate rates of provider supply at the PCSA level. These counts were used to calculate the number of primary care providers (physicians, NPs, and PAs) per 100,000, which in turn was converted into centile scores such that a higher score indicates fewer providers, creating a measure of workforce scarcity.

We also used an age-sex-race adjusted measure of avoidable hospitalizations from the 2007 Dartmouth Atlas. Avoidable hospitalization rates refer to the percentage of hospitalizations that were for ambulatory care sensitive conditions—exemplified by asthma, diabetes, chronic obstructive pulmonary disease, and congestive heart failure—where proper and timely primary care could reduce the likelihood of a hospitalization. There is considerable regional variation in overall hospitalization rates due in part to the supply of hospital beds (Goodman et al. 2009). To address this issue, instead of avoidable hospitalization rate, we calculated the percentage of all hospitalizations that were for an ambulatory care sensitive condition. This measure is available for 6,421 of 6,538 PCSAs. One limitation of this measure is that it is based on elderly Medicare recipients. In preliminary work, we also examined avoidable hospitalization rates from the Healthcare Cost and Utilization Project (HCUP), which includes patients of all ages but is only available for 13 states with patient zip code information. We found a strong correlation between the Dartmouth PCSA measure and the HCUP measure ($r = 0.76$).

While all of the above ACS measures are available at either the census tract or block group level, this is currently not the case for insurance status, which was first measured starting in 2008. Currently, the uninsured measure is only available in the 2009 ACS 1-year estimates and only for counties with a population greater than 60,000 ($n = 2{,}613$). For smaller counties ($n = 506$), we used 2007 Small Area Health Insurance Estimates developed by the Census Bureau (http://www.census.gov/did/www/sahie/). Our results below did not change substantially if we restricted our analysis only to the larger counties with an ACS insurance measure. These county-level uninsured rates were then used to calculate PCSA-level rates.

In our multivariate analyses, we added 5-year ACS measures of the percent foreign born and percent Hispanic. Finally, we created dichotomous indicator of rurality based on the rural–urban continuum classification codes for each county (http://www.ers.usda.gov/Data/RuralUrbanContinuumCodes/).

Design

Developing the Social Deprivation Index. In our first step, we first converted all of our sociodemographic measures into centiles to facilitate interpretation of the results across measures by creating a common underlying scale (Eibner and Sturm 2006; Ricketts et al. 2007; Noble et al. 2008). Second, we performed a factor analysis on the nine social deprivation measures identified. Factor analysis assumes a common dimension (unobserved) underlying all variables and creates a summary measure to capture this commonality. This requires variables to be correlated, and it is this degree of correlation that factor analysis is trying to capture. Because of the substantial variation in population size across PCSAs, all analyses were weighted by PCSA population. On the basis of the above analysis, we constructed a parsimonious index retaining items that had a partial correlation above 0.60. Our final step was to use the factor loadings to construct weighted factor scores for each index.

Relationship between Social Deprivation Index and Measures of Access and Health Outcomes. As a preliminary assessment of the different indices, a pairwise correlation analysis was conducted between our index of deprivation, measures of health care outcomes (mortality, infant mortality, low birth weight, diabetes), and measures of primary health care access (avoidable hospitalizations, availability of health care providers, uninsured and rurality). As with the measures used in our factor analysis, we converted all these measures (with the exception of rurality) to centile rankings. We obtained similar results without this transformation.

To test the reliability of the SDI as a predictor of health outcomes, for each health outcome (diabetes, age-adjusted mortality, infant mortality, and low birth weight) we used three models to test the robustness of our findings. In the first model, SDI is the only independent variable and corresponds to the unadjusted bivariate relationships. Because other factors not captured by the SDI index also may influence health outcomes, the second model controls for some of these, specifically known access-related measures: workforce scarcity, uninsured, avoidable hospitalizations, and rurality. Given the suspected confounding effects of ethnicity and immigration status, the third model builds on the second by adding percent Hispanic and percent foreign born to test the significance of the SDI when these factors are accounted for. Finally, to examine the value of a multidimensional approach to social deprivation, we compare the effect of the SDI on health outcomes with the effects of simpler single dimension measure of poverty.

Statistical Analysis. We used the statistical software Stata, version 12.0. Given that state-level policies (notably Medicaid) impact both our independent and dependent variables, we adjusted standard errors for clustering of PCSAs within states and we used the *vce* (*cluster* clustvar) option in the regression command. This allows for intragroup correlation, relaxing the requirement that the observations be independent. For our final comparison of the effects of SDI compared with effect of poverty only, we used bootstrapping techniques to compare the differences in R^2 (Jeong 2006). In the analysis, we used the *bootstrap* command in Stata, with 1,000 replications in which we obtained the standard error and confidence intervals of the difference in R^2.

Results

Descriptive statistics for the variables used in our analysis are shown in Table 1. With a few exceptions, these measures are approximately normally distributed. Reflecting high levels of residential segregation in the United

Table 1: Summary of Measures Used in Analysis

Measures	*Mean*	*SD*	*P25*	*P50*	*P75*	*Source*
Index measures						
Percent poor	13.67	6.8	8.99	12.68	16.97	5-Year ACS (2005–2009)
Percent nonemployed	7.54	2.68	5.75	7.16	8.75	5-Year ACS (2005–2009)
Percent single parent	18.51	6.04	14.5	17.78	21.46	5-Year ACS (2005–2009)
Percent black	12.36	15.44	2.1	6.35	16.49	5-Year ACS (2005–2009)
Percent high-need age group	40.09	2.33	38.86	40.06	41.24	5-Year ACS (2005–2009)
Percent <12 years schooling	15.85	8.3	10.11	14.11	19.86	5-Year ACS (2005–2009)
Percent no car	8.6	9.75	4.41	6.06	8.77	5-Year ACS (2005–2009)
Percent renter occupied	32.69	12.86	24.02	30.45	38.72	5-Year ACS (2005–2009)
Percent crowding	3.44	3.93	1.24	2.08	3.87	5-Year ACS (2005–009)
Health outcomes						
Age-adjusted mortality/1,000	8.06	1.19	7.26	7.96	8.74	CDC wonder (2005–2007)
Percent diabetes (age adjusted)	8.57	1.5	7.54	8.4	9.57	CDC (2008)
Low birth rate/100 births	7.93	1.5	6.96	7.67	8.58	Area resource file (2008)
Infant mortality/1,000 births	6.86	2.24	5.4	6.53	7.91	Area resource file (2008)
Access-related measures						
Percent uninsured	17.03	5.9	12.73	16.72	20.69	1-Year ACS (2009)/Census Bureau SAHIE (2007)
Percent avoidable hospitalization	20.5	3.32	18.37	20.35	22.29	Dartmouth Atlas (2007)
Provider/100,000	91.41	52.78	62.25	84.12	107.23	AMA Masterfile (2010)/NPI (2010)
Rural (0,1)	0.17	0.37				USDA RUCC (2003)
Control variables						
Percent Hispanic	15.09	18.05	2.82	7.79	20.94	5-Year ACS (2005–2009)
Percent foreign born	12.39	11.66	3.59	8.16	18.28	5-Year ACS (2005–2009)

Note. PCSAs are the unit of analysis (n = 6,538). Data are weighted by PCSA population. High-need age group refers to children under age of 5 and women between the ages of 18 and 44.

ACS, American Community Survey; AMA, American Medical Association; CDC, Center for Disease Control; NPI, National Provider Identifier. P25, P50, P75, 25th, 50th (median), and 75th percentile, respectively; SAHIE, Small Area Health Insurance Estimates; USDA RUCC, U.S. Department of Agriculture Rural Urban Continuum Classification.

States, percent black, Hispanic, and foreign born are skewed (with medians substantially lower than the means). In preliminary analyses, results obtained using log transformations of these skewed measures did not differ substantially from those obtained transforming the measures to centile rankings. Our factor analysis identified a single factor describing social and material deprivation that includes single parent families, poverty, percent with less than a high school diploma, nonemployed, and no car ownership (Table 2). Details of the full factor analysis are available from the authors on request. The percent of population in high-need age/sex groups and percent black had relatively low factor loadings (<0.60) and were excluded from the reduced index.

The pairwise correlations indicate that our SDI is, as expected, positively and significantly ($p < .01$) associated with mortality, low birth weight, infant mortality, diabetes prevalence, and ambulatory care sensitive hospitalizations (Table 3). There is no significant correlation between this index and the supply of primary care providers or with rurality. It is of interest to examine the pairwise association between measures of access and health outcomes. Avoidable hospitalizations are positively associated with both mortality ($r = 0.356$) and diabetes ($r = 0.333$); the association with infant mortality and low birth weight is weaker but still positive and significant. Likewise, uninsured is positively associated with each of the health outcomes but all of the correlation coefficients are below 0.20. In contrast, and consistent with the findings of other studies (Lara et al. 2005; Arias 2010; Castro et al. 2010), both the Hispanic and foreign-born measures are negatively associated with health outcomes. The results for the workforce measure are mixed. There is a positive association between workforce scarcity and mortality ($r = 0.176$) as well

Table 2: Factor Loadings of Social Deprivation Items

	Factor Loadings	
	Full	*Reduced*
Less than 12 years schooling	0.753	0.778
Black	0.511	
Crowding	0.609	0.640
High need age group	0.379	
No car	0.760	0.733
Nonemployed	0.704	0.707
Poor	0.828	0.828
Renter occupied	0.734	0.727
Single parent	0.861	0.835

Note. The level of analysis is PCSAs (n = 6,358). All measures are converted to centile rankings.

Table 3: Pairwise Correlation Matrix of Social Deprivation Index (SDI) and Measures of Health Outcomes and Access

	SDI	*Mortality*	*Diabetes*	*Infant Mortality*	*LBW*	*Avoid. Hosp.*	*Uninsured*	*Hispanic*	*Foreign Born*	*WF Scarcity*
Mortality	0.455*									
Diabetes	0.308*	0.615*								
Infant mortality	0.433*	0.633*	0.598*							
LBW	0.471*	0.538*	0.581*	0.600*						
Avoid. Hosp.	0.335*	0.357*	0.333*	0.182*	0.242*					
Uninsured	0.233*	0.143*	0.179*	0.131*	0.143*	0.034*				
Hispanic	0.388*	−0.147*	−0.258*	−0.128*	−0.042*	−0.000	0.345*			
Foreign born	0.260*	−0.315*	−0.313*	−0.265*	−0.094*	−0.103*	0.186*	0.838*		
WF scarcity	0.042	0.176*	0.172*	0.057*	0.008	0.287*	0.137*	0.064	−0.106*	
Rural	0.001	0.162*	0.108*	0.096*	−0.001	0.246*	−0.000	−0.315	−0.452*	0.125*

Note. PCSAs are the unit of analysis. The number of observations for each measure is 6,538 with the exception of avoidable hospitalizations (n = 6,421). All measures, except for rural, are converted to centiles rankings.

*$p < .01$.

LBW, low birth weight; WF, workforce.

as diabetes (r = 0.172), but much weaker associations with infant mortality and low birth weight. There is a similar pattern for our indicator of rurality: mortality, diabetes, and infant mortality rates are slightly higher in rural PCSAs than urban PCSAs; there is no urban–rural difference in low birth weight rates.

The next step in our analysis is to examine whether these patterns hold in multivariate models (Table 4). The first set of models only includes the SDI measure. The second set shows that SDI still has a positive relationship with each of the health outcomes controlling for workforce scarcity, rates of avoidable hospitalizations, uninsured, and rurality. Comparing the first and second models, we find a decrease in the magnitude of the SDI coefficient, especially for mortality and diabetes. For instance, the SDI coefficient in the diabetes models decreases from 0.309 to 0.201. The third model produced negative coefficients for Hispanic and foreign born. After adding these measures to the model, the SDI coefficient increases substantially. For instance, the SDI coefficient increases from 0.379 in Model 2 to 0.506 in Model 3. A similar increase is evident for the other three health outcomes. This indicates that better health outcomes in areas with more Hispanics and foreign-born persons confound the effect of SDI as a predictor of health outcomes. Given the greater likelihood that Hispanic/foreign born are uninsured, it is not surprising to find a similar confounding of the effect of uninsured on health outcomes. For example, the uninsured coefficient increases in magnitude from Model 2 to Model 3 across all outcomes and becomes statistically significant in all but one.

Overall, this demonstrates that our SDI measure remained significant when controlling for a range of important confounders or other explanatory variables across each of our four health outcomes. On closer inspection of each of the models, it is apparent that an increase of one percentile in SDI results in a greater increase in a health outcome (for example mortality) than a one percentile shift in another explanatory variable in most cases with a few exceptions. This would suggest that the health outcomes examined are more responsive to changes in SDI than the other measures examined. Further analysis is required to explore this relationship.

The final step in our analysis is to compare our multidimensional measure of deprivation to poverty alone, the sole deprivation measure that underpins the current MUA designation. In Table 5, for each health outcome, we report first the poverty coefficient in models with the full set of controls from the third full models in Table 4. To ease interpretation, we report again the SDI coefficients from these full models. Given the high correlation between our SDI measure and poverty (r = 0.86), we would expect a similar effect of poverty on health outcomes to that of SDI in this multivariate analysis. In

Table 4: OLS Regression Models for Relationship between Health Outcomes and Social Deprivation Index (SDI) and Other Measures of Access

	Coefficient (1)	*SE*	*Coefficient (2)*	*SE*	*Coefficient (3)*	*SE*
(A) Mortality						
SDI score	0.450**	0.047	0.379**	0.044	0.506**	0.033
Workforce scarcity			0.092*	0.038	0.063	0.042
Uninsured			0.036	0.065	0.106*	0.047
Avoidable hospitalization			0.176**	0.048	0.142**	0.049
Rural (0,1)			8.266**	2.735	−7.942**	1.614
Hispanic					−0.015	0.088
Foreign born					−0.479**	0.094
Constant	27.730**	2.429	14.654**	4.666	35.557**	4.754
R-squared	0.20		0.27		0.44	
(B) Diabetes						
SDI score	0.309**	0.073	0.201**	0.068	0.388**	0.046
Workforce scarcity			0.078	0.039	0.101**	0.030
Uninsured			0.115	0.073	0.245**	0.058
Avoidable hospitalization			0.230**	0.057	0.189**	0.048
Rural (0,1)			3.263	4.188	−11.450**	1.723
Hispanic					−0.437**	0.097
Foreign born					−0.132	0.093
Constant	34.688**	3.872	18.286**	5.850	34.306**	7.416
R-squared	0.09		0.18		0.38	
(C) Infant mortality						
SDI score	0.433**	0.061	0.421**	0.057	0.547**	0.031
Workforce scarcity			0.021	0.022	−0.006	0.022
Uninsured			0.030	0.062	0.100	0.054
Avoidable hospitalization			0.012	0.044	−0.022	0.037
Rural (0,1)			6.977*	3.448	−8.786**	1.577
Hispanic					−0.028	0.069
Foreign born					−0.457**	0.091
Constant	28.605**	2.309	24.898**	4.428	45.138**	4.013
R-squared	0.19		0.20		0.36	
(D) Low birth weight						
SDI score	0.471**	0.076	0.423**	0.074	0.536**	0.042
Workforce scarcity			−0.048	0.029	−0.038	0.028
Uninsured			0.047	0.061	0.124*	0.055
Avoidable hospitalization			0.118*	0.058	0.093	0.052
Rural (0,1)			−1.926	4.114	−11.494**	1.745
Hispanic					−0.239*	0.110
Foreign born					−0.118	0.108
Constant	26.680**	2.607	23.511**	4.763	34.243**	6.883
R-squared	0.22		0.23		0.31	

Note. Standard errors (SE) are adjusted for clustering within states. PCSAs are the unit of analysis (n = 6,358). Models 2 and 3 include a flag for PCSAs with missing avoidable hospitalization rates.
*p < .05; **p < .01.

Table 5: Comparison of Social Deprivation Index (SDI) and Poverty Rate as Predictors of Health Outcomes: OLS Regression Coefficients

	Age-Adjusted Mortality		*Diabetes*		*Infant Mortality*		*Low Birth Weight*	
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
Poverty	0.415** (0.028)	–	0.326** (0.035)	–	0.462** (0.027)	–	0.450** (0.034)	–
SDI score	–	0.506** (0.033)	–	0.388** (0.046)	–	0.547** (0.031)		0.536** (0.042)
R-squared	0.388	0.441	0.354	0.381	0.306	0.359	0.261	0.314
Difference in R^2	0.053 (0.037–0.070)**		0.027 (0.015–0.039)**		0.053 (0.035–0.071)**		0.053 (0.033–0.072)**	

Note. Standard errors (SE) in parentheses. SEs are adjusted for clustering within states. PCSAs are the unit of analysis (n = 6,358). All models include controls for uninsured, avoidable hospitalization, missing avoidable hospitalization, Hispanic, and foreign born (see Table 4). The SDI score coefficients correspond to those of models 3 in Table 4.
To test difference in R^2 for the two alternative, nonnested models, we obtained standard errors by bootstrapping the difference for the four outcomes, using 1,000 replications and a sample size of 6,358. The 95% confidence intervals of the differences are in brackets.
$^{**}p < .01$.

comparing SDI with poverty across all measures, our bootstrap results indicate that the R^2 (the percent of variance explained) is always significantly higher for the SDI models than the poverty models. Further exploration to test whether this difference is significant for policy application would be helpful.

DISCUSSION

This study demonstrates the potential value of a composite but parsimonious SDI within rational areas of health care service. This is the first study to apply an index of this kind across all U.S. Primary Care Service Areas, hereby linking an important measure of need with an underlying rational geography area based on patient care-seeking behavior. The relationship between social deprivation and poor health outcomes and access is reliable and strong at this level of geography. Given efforts to improve shortage and underservice designations in the United States, and the rational service area definitions to which these are tied, this composite SDI measure offers potential use as a geographic planning and resource allocation tool that reflects how services are currently delivered and accessed. In this regard, it reflects how related tools are used in other countries and offers elements that they may want to test in their current tools.

The positive relationship between SDI and mortality, low birth weight, infant mortality, and diabetes persists after controlling for other measures of access. Our models also suggest that the health outcome measures are more responsive to changes in SDI than the other important determinants of health outcomes examined.

A composite measure of social deprivation such as this one can be a complementary indicator of medical underservice and resource need. The multidimensional aspect of the SDI is important. Our models have shown that the SDI provides a significant though modest improvement on poverty. Currently, poverty is the sole measure of deprivation in the designation of U.S. medically underserved areas, in contrast to the multidimensional measures that distinguish areas of need in many peer nations (Townsend 1987; Adhikari 2008; Noble et al. 2008; White et al. 2008).

In our models, a change in workforce scarcity compared with SDI results in a smaller change in our outcome measures. Changes in uninsurance also results in similar small but significant changes in most of the health outcomes, particularly after adjusting for ethnicity. The health outcomes examined were generally more responsive to shifts in the avoidable hospitalization measure than either workforce scarcity or uninsurance. Avoidable hospitalizations may be more closely associated with health outcomes when the population in greatest need cannot effectively access more appropriate health care services.

It is important to note the confounding effect on the four outcome measures examined of percent Hispanic and percent foreign born in our multivariate models. We found a negative association with health outcome and access measures, as previously described in the literature (Lara et al. 2005; Arias 2010; Castro et al. 2010). As such, we have added these measures as controls, which results in larger coefficients for SDI in determining health outcomes.

Combined with other indicators, a measure of social deprivation has potential application for identifying and prioritizing areas in need of additional health care resources. Its use could facilitate prioritization of existing programs, such as community health center grants and National Health Service Corps assignments. The SDI developed by this study also permits comparing observed outcomes against those expected based on our model, identifying areas with outcomes that are better or worse than expected. This may allow identification of other factors that influence these health outcomes. Adequate exploration of this interesting possibility is beyond the scope of this study.

We demonstrated that the SDI is correlated with population health outcome measures. Many programs are targeted to particular conditions, sectors of the population, or health system problem (such as workforce shortage). In this circumstance, different combination of measures (of need, access, and outcomes) may be useful for targeting resources for particular programs (Ricketts et al. 2007; Noble et al. 2008; Rae 2009). An example of this is eligibility criteria for a National Health Service Corps physician, which includes measures of poverty, infant mortality, and travel distance to nearest primary care provider (Federal Register 2010). An international example uses a measure that includes health outcomes as well as social deprivation, for identifying areas for additional funding (Noble et al. 2008). The SDI also may be useful in combination with other measures in this way. This flexible approach has the potential to better align specific community needs with policy options.

Limitations

A limitation of this study is that our outcome measures (and some measures of access such as avoidable hospitalizations and uninsurance) are by necessity estimates based on county measures. In assigning these measures to a lower geography, we potentially mask the likely variation and heterogeneity within counties and between PCSAs. As such, it is possible that the relationships of the SDI in our models may be stronger. Another limitation is the low percent variance explained in our models. Again, this is possibly a function of the limitation of the health outcome estimates. Better data at a lower geography are needed to test this, which is currently unavailable. However, it should be noted that the variance explained is comparable with previous work (Wang and Luo 2005; Salmond, Crampton, and Atkinson 2007).

PCSAs were selected for testing due to their reflection of primary care utilization patterns, but there are limitations to using a singular geography based on utilization by an older and relatively well-insured population. Health utilization behaviors are not always constrained within a predictable geographic envelope, and PCSAs may not reflect the care-seeking behaviors of some non-Medicare populations, particularly uninsured or underinsured people. As discussed above, PCSAs also present a problem for certain data elements that are not captured at this geography and have to be reconfigured based on assumptions or imputations.

Conclusion

There is an urgent need in the United States to address equity and access through reform of the policy agenda, within which primary health care services play a key role. The willingness to realign resource allocation with need in the United States should be paired with the development of tools to understand better where need is greatest. Given the political nature of such allocation, it is important that there is an evidence-based justification for the manner of determining where resources go and do not go. The analysis presented here demonstrates positive associations of a PCSA-level composite SDI with measures of access and health outcomes. The relationship with health outcomes remains significant when controlling for access variables. This represents an important preliminary step in determining whether SDI improves prediction of health outcomes when compared with other measures of social deprivation (such as poverty) when (1) incorporated into current shortage and underservice designations, and (2) utilizing alternative, underlying rational service area geographies. This has important implications as federal policy makers debate updating decades-old methods of assigning areas of need and a rational means of health care resource allocation for more equitable distribution.

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Supporting Information

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Appendix SA1: Author Matrix.

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